Active Learning Through Chest X-ray Imaging

CS 4850-01/03/04, Fall 2025
Presented November 4th, 2025
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Prototype Presentation Presented by

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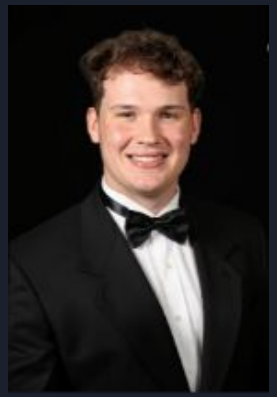
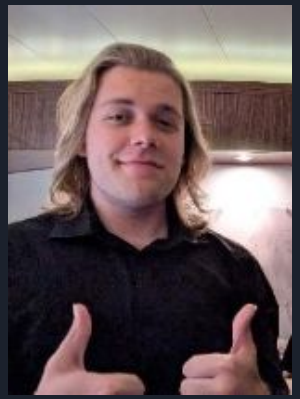
Introductions

Josh Smith
Team Leader
Development



Elijah Merrill
Development



Noah Lane
Documentation

Mathew Hall
Documentation

Overview

- General Motives and Goals
- Required documents
- Code explanation
- Future works

Motive

- Originally idealed on Satellite Image Dataset
- The strive to have an outstanding project to present to the tech industry
- To experiment with new software and obtain an understanding
- To build an image classification system that would be dynamic and would work with many datasets rather than one

SDLC - Requirements

Functional Requirements

- Load and preprocess Chest X-ray dataset.
- Train baseline model using transfer learning.
- Implement active learning loop with uncertainty sampling.
- Evaluate performance (Accuracy, F1, AUC-ROC, AUC-PR).
- Provide user interface for training, labeling, and visualization.

Non-Functional Requirements

- Modular, maintainable, and well-documented codebase.
- Simple, intuitive user interface.
- Efficient performance on GPU-enabled systems.
- Cross-platform (Windows, macOS, Linux).
- Compatible with TensorFlow or PyTorch frameworks.

SDLC - Design

Design Considerations

- Uses public, locally stored datasets for privacy and performance.
- Requires modern OS and CPU for smooth image processing.
- Interface supports both experts and beginners.
- Future updates may enhance accuracy and efficiency.

Architectural Strategies

- Modular structure: Data, Training, Active Learning, Evaluation, UI.
- Python-based (PyTorch, NumPy, Pandas, Matplotlib).
- Employs CNNs and uncertainty sampling for model training.
- Focus on scalability, maintainability, and robust error handling.

SDLC - Development

Data Pipeline

- Indexer.py - builds table linking images
- Splitter.py - divides dataset by unique patient IDs
- Preprocess.py - applies resize / normalize / augmentation
- Dataset.py - loads transformed image-label pairs into PyTorch

Supporting Components

- Config.yaml - central parameters (paths, classes, image size, splits)
- Smoke.py - verifies entire pipeline functionality before training
- Frameworks/Libraries - Pytorch, Pandas, NumPy, Pillow, TorchVision, TQDM
- Dataset Source - NIH Chest X-ray (Kaggle)

Indexer

- Links each image filename to its full file path on disk
- Rename columns & standardizes labels so downstream code can use them cleanly
- Builds a DataFrame that maps various parameters
- Acts as a “single source of truth “ for dataset structure

```
#join the root path with CSV filename to get full path
csv_path = os.path.join(data_root, 'Data_Entry_2017.csv')
#check if the CSV file exists. if not, programs stops and raise error
if not os.path.exists(csv_path):
    raise FileNotFoundError(f"Missing {csv_path}")

#load the CSV metadata into a DataFrame
meta = pd.read_csv(csv_path)

#rename columns for cleaner access within python
meta = meta.rename(columns={
    "Image Index": "image_id", #filename of x-ray image
    "Finding Labels": "label_raw", #original string of disease labels
    "Patient ID": "patient_id", #id of the patient
    "View Position": "view" #x-ray view type (PA, AP, etc)
})
```

```
#walk through the directory and build a map of filenames -> absolute paths
path_map = {}
for root, _, files in os.walk(img_dir):
    for f in files:
        #include only png/jpp/jpeg files (ignoring others)
        if f.lower().endswith((".png", ".jpg", ".jpeg")):
            path_map[f] = os.path.join(root, f)

#map each image_id from the CSV to its actual file path
meta["path"] = meta["image_id"].map(path_map.get)
#create a boolean column showing which images are missing
meta["missing"] = meta["path"].isna()
```

Splitter

- Divides the dataset into three sets: train / validation / test sets
- Splits by unique Patient IDs rather than by individual images
- Ensures that no patient appears in multiple splits
- Adds a new “split” column to the dataset

```python
#split dataset into train/validation/test sets using patient ids rather than individual images to avoid data leaking where a patient
def split_by_patient(df: pd.DataFrame, ratios=(0.7,0.15,0.15), seed=42):  4 usages
    #safety check to ensure ratios sum to 1.0 (with tolerance)
    assert abs(sum(ratios) - 1.0) < 1e-6
    #create a reproducible random generator
    rng = np.random.default_rng(seed)
    #collect unique patient ids
    patients = df["patient_id"].dropna().unique()
    #shuffle patient ids randomly
    rng.shuffle(patients)

    #compute how many patients go into each split
    n = len(patients)
    n_train = int(ratios[0] * n)
    n_val = int(ratios[1] * n)

    #slice the shuffled list into three sets
    train_p = set(patients[:n_train])
    val_p = set(patients[n_train:n_train+n_val])
    test_p = set(patients[n_train+n_val:])
```

```python
    #helper function that assigns a split label based on patient id
    def assign(pid):
        if pid in train_p: return "train"
        if pid in val_p: return "val"
        return "test"

    #make a copy so the orginal DataFrame not modified directly
    df = df.copy()
    #apply the split assignment to every row
    df["split"] = df["patient_id"].map(assign)
    #sanity check to ensure we have exactly three split categories
    assert set(df["split"].unique()) == {"train", "val", "test"}
    #return updated DataFrame and a quick summary of patient counts
    return df, {"train": len(train_p), "val": len(val_p), "test": len(test_p)}
```

Preprocess

- Prepares image data for PyTorch
  - Uses torchvision.transforms()
  - Resizing
  - Cropping
  - Normalization
- Applies random flips and rotations to boost dataset diversity

```
#flips image horizontally and rotates image slightly
t += [transforms.RandomHorizontalFlip(p=0.5),
      transforms.RandomRotation(degrees=5)]
#scale the image to input size model expects
t += [transforms.Resize(input_size, antialias=True),
      transforms.ToTensor()]
#add normalization (optional)
if use_imagenet_norm:
    t += [transforms.Normalize(mean=[0.485, 0.456, 0.406],
                               std=[0.229, 0.224, 0.225])]
#combine all transformations into a single callable pipeline
return transforms.Compose(t)
```

Dataset

- Connects preprocessed data to the model's training process
- Loads x-ray images and converts them to RGB
- Turns images and labels into PyTorch tensors

```
class CXRDataset(Dataset):
    def __init__(self, index_df: pd.DataFrame, split: str, class_names, transforms):
        self.df = index_df[index_df["split"] == split].reset_index(drop=True)
        self.class_names = class_names
        self.t = transforms

    def __len__(self): return len(self.df)

    def __getitem__(self, i: int):
        row = self.df.iloc[i]
        img = Image.open(row.path).convert("RGB") #ensure 3-channel
        x = self.t(img)
        y = torch.tensor(row[self.class_names].values.astype("float32"))
        meta = {"image_id": row.image_id, "patient_id": row.patient_id}
        return x, y, meta
```

Config

- .yaml file that controls all main settings – dataset paths, preprocessing, and data splits

- Allows for pipeline easy configuration

```yaml
data:
  # list of class names from the dataset
  class_names:
    - Atelectasis
    - Cardiomegaly
    - Effusion
    - Infiltration
    - Mass
    - Nodule
    - Pneumonia
    - Pneumothorax
    - Consolidation
    - Edema
    - Emphysema
    - Fibrosis
    - Pleural_Thickening
    - Hernia
```

Smoke

- End-to-end integration test of the entire data pipeline
- Confirms tensor dimensions (N, C, H, W) match the expected CNN input size
- Runs before any real model training to catch issues early

```python
from torch.utils.data import DataLoader
from src.data.indexer import build_index, filter_views
from src.data.splitter import split_by_patient, save_splits_json
from src.data.preprocess import make_transforms
from src.data.dataset import CXRDataset

def main(cfg_path = "config.yaml"):  1 usage
    cfg = yaml.safe_load(open(cfg_path))
    root = cfg["paths"]["data_root"]
    cls  = cfg["data"]["class_names"]
    keep = cfg["data"]["keep_views"]
    h, w = cfg["model"]["input_size"]
```

Outputs

```
(.venv312) PS D:\School Files\School Notes\Fall 2025\CS 4850\Project Testing On My System\active_learning_system_on_host> python -m src.data.smoke
Building index:
Images in CSV: 112,120; missing paths: 0
Splitting by patient:
Patients per split: {'train': 21563, 'val': 4620, 'test': 4622}
D:\School Files\School Notes\Fall 2025\CS 4850\Project Testing On My System\active_learning_system_on_host\.venv312\Lib\site-packages\torch\utils\data\dataloader.py:668: UserWarning: 'pin_memory' argument is set as true but no accelerator is found, then device pinned memory won't be used.
  warnings.warn(warn_msg)
Train batch: x=(8, 3, 224, 224), y=(8, 14) (N,C,H,W) = torch.Size([8, 3, 224, 224])
Example metas: {'image_id': ['00020691_003.png', '00002350_010.png', '00019407_007.png', '00015071_002.png', '00006013_003.png', '00019718_000.png', '00012280_013.png', '00021031_001.png'], 'patient_id': tensor([20691,  2350, 19407, 15071,  6013, 19718, 12280, 21031])}
(.venv312) PS D:\School Files\School Notes\Fall 2025\CS 4850\Project Testing On My System\active_learning_system_on_host>
```

Outputs

splits.json

File Edit View


```
{
  "counts": {
    "train": 78934,
    "val": 16871,
    "test": 16315
  },
  "patients_per_split": {
    "test": 4622,
    "train": 21563,
    "val": 4620
  }
}
```


image_id - str	label_raw - str	Follow-up # - i64	patient_id - i64	Patient Age - i64	Patient Gender - str	view - str	OriginalImage[Width - i64	Height] - i64	OriginalImageI
00000001_000.png	Cardiomegaly	0	1	58	M	PA	2682	2749	0.143
00000001_001.png	Cardiomegaly|Emphysema	1	1	58	M	PA	2894	2729	0.143
00000001_002.png	Cardiomegaly|Effusion	2	1	58	M	PA	2500	2048	0.168
00000002_000.png	No Finding	0	2	81	M	PA	2500	2048	0.171
00000003_000.png	Hernia	0	3	81	F	PA	2582	2991	0.143
00000003_001.png	Hernia	1	3	74	F	PA	2500	2048	0.168
00000003_002.png	Hernia	2	3	75	F	PA	2048	2500	0.168
00000003_003.png	Hernia|Infiltration	3	3	76	F	PA	2698	2991	0.143
00000003_004.png	Hernia	4	3	77	F	PA	2500	2048	0.168
00000003_005.png	Hernia	5	3	78	F	PA	2686	2991	0.143
00000003_006.png	Hernia	6	3	79	F	PA	2992	2991	0.143
00000003_007.png	Hernia	7	3	80	F	PA	2582	2905	0.143
00000004_000.png	Mass|Nodule	0	4	82	M	AP	2500	2048	0.168
00000005_000.png	No Finding	0	5	69	F	PA	2048	2500	0.168
00000005_001.png	No Finding	1	5	69	F	AP	2500	2048	0.168
00000005_002.png	No Finding	2	5	69	F	AP	2500	2048	0.168
00000005_003.png	No Finding	3	5	69	F	PA	2992	2991	0.143
00000005_004.png	No Finding	4	5	70	F	PA	2986	2991	0.143
00000005_005.png	No Finding	5	5	70	F	PA	2514	2991	0.143
00000005_006.png	Infiltration	6	5	70	F	PA	2992	2991	0.143
00000005_007.png	Effusion|Infiltration	7	5	70	F	PA	2566	2681	0.143
00000006_000.png	No Finding	0	6	81	M	PA	2500	2048	0.168
00000007_000.png	No Finding	0	7	82	M	PA	2500	2048	0.168
00000008_000.png	Cardiomegaly	0	8	69	F	PA	2048	2500	0.171
00000008_001.png	No Finding	1	8	70	F	PA	2048	2500	0.171
00000008_002.png	Nodule	2	8	73	F	PA	2048	2500	0.168
00000009_000.png	Emphysema	0	9	73	M	PA	2992	2991	0.143
00000010_000.png	Infiltration	0	10	84	F	PA	2992	2991	0.143
00000011_000.png	Effusion	0	11	75	M	PA	2638	2449	0.143
00000011_001.png	No Finding	1	11	75	M	PA	2500	2048	0.168
00000011_002.png	No Finding	2	11	75	M	PA	2714	2781	0.143
00000011_003.png	No Finding	3	11	75	M	PA	2500	2048	0.168
00000011_004.png	No Finding	4	11	75	M	PA	2500	2048	0.168

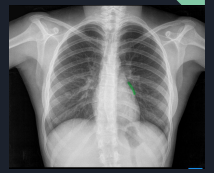
Set-Up Process

- The project includes six essential source files found in the “source code” folder of the GitHub repository.
- The dataset can be downloaded from Kaggle – NIH Chest X-Rays. After extraction, store the “archive” folder alongside the source files or record its full path for configuration.
- The system requires Python version 3.10 or later and several key packages: torch, torchvision, torchaudio, pandas, pyarrow, numpy, tqdm, and matplotlib.
- Verify that dataset and output paths match your local directory structure, updating any file references as needed.
- To confirm successful setup, run python smoke.py.

Database Connection

- The system does not use a traditional database connection. Instead, it relies on a file-based data storage approach managed locally on the user’s system.
- A publicly available chest X-ray dataset serves as the primary data source for model training, validation, and testing.
- All image files and labels are loaded directly from local directories or structured folders rather than through a database.
- This design ensures simpler configuration, faster access, and greater portability across systems.

Future Development Overview (CNN)



Testing
VS
Training

A	B	C	D	E
37	21	28		45
20	24	21	1	20
17	13	18		27
5	33	17		18
14	16	12	2	28
14	13	14	1	26
16	13	19	2	18
12	16	9	1	28
11	15	12		12
5	7	12		15

Input dataset and/or image

Pre-processing and data labeling

Transfer data into usable data

Node (1, 1)

Node (n, 1)

Node (1, m)

Node (n, m)

Confidence value received from CNN

Interpre-tation of the data

"Healthy"

Training and Testing Data

- 70% training data - data to train the CNN
- 15% validation data - data to sure that the data fits in accordance to the rest of the set
- 15% testing data - data put against the training data to see if our program is working correctly

Summary

- What motivated us
- SDLC Documents
- Data processing pipeline
- Future work/phases
- We submitted our powerpoint slides prior to this presentation.